A Systematic Literature Review on Machine Learning Algorithms for LoRaWAN Network Optimization: Current Trends and Future Directions

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Abstract. The long-range communication and energy efficiency of LoRaWAN have enabled it to be a significant Low Power Wide Area Network (LPWAN) technology in the fast-growing Internet of Things (IoT). Nevertheless, LoRaWAN faces very severe technological challenges as the density of the network increases, i.e., loss of packets and limited scalability in large-scale implementation cases. Traditional network management methods, such as Adaptive Data Rate (ADR), are often not reliable in dynamic and uncertain environments. As a result, there is a growing trend toward incorporating Machine Learning (ML) to improve network performance via intelligent adaptation. The purpose of this Systematic Literature Review (SLR) is to determine and examine the most popular algorithmic trends for LoRaWAN optimization. The results offer a thorough classification of existing intelligent solutions and point out unresolved research issues, acting as a guide for creating LoRaWAN frameworks that are more robust and self-optimizing in the context of Industry 4.0.

Keywords: Internet of Things, LoRaWAN, Machine Learning, Network Optimization, Systematic Literature Review

1 Introduction

The Fourth Industrial Revolution (4IR) is the term used to describe how emerging technologies are used to disrupt industries. It is distinguished by cutting-edge technology that combines the physical, biological and digital realms, influencing all fields, sectors, and the economy [1]. IR4.0, in which connected technology allows the digital and physical realms to mix [2]. The way information technology is used in Malaysia has changed, especially with regard to cloud computing, system integration, and the Internet of Things (IoT). The IoT is a widely used system that connects people, things, processes, data, and the Internet to one another [3]. The IoT ecosystem uses a variety of deployment scenarios, including high-speed mobile apps, stationary sensing, and slow-moving industrial monitoring. Every one of these scenarios has unique networking

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goals and operational needs [4]. In recent years, as digital and physical devices have been linked to provide simpler information sharing and service capabilities, the proliferation of IoT devices has continued to grow. The use of flexible IoT devices to evaluate knowledge from cyber, which involves physical systems across many different applications. IoT-enabled devices are being employed extensively in a variety of industrial industries as their costs continue to decline [5]. From [6], sensors, connectivity, and computation are just a few of the participating entities that have greatly expanded as IoT has developed. IoT is poised to change every significant element of our residences, healthcare, automation, transportation, cities, grids, manufacturing, and agriculture.

The IoT is a quickly changing field, and many connectivity standards have arisen to satisfy the needs of different applications, from energy-efficient protocols to high-bandwidth cellular networks. Though they offer ultra-low latency and massive data throughput necessary for real-time applications like autonomous vehicles and augmented reality, 5G and the upcoming 6G technologies are less suitable for basic, battery-operated sensors due to their high operating costs and significant power consumption [7]. Low Power Wide Area Networks (LPWAN), a category created especially for long-range transmission with low energy consumption, successfully fill this gap. Due to its low power, long range, and inexpensive communication features, LPWAN is becoming more and more well-liked in research and industrial sectors. Long-range communication is possible up to 10–40 km in rural areas and 1–5 km in urban areas [8]. In early 2013, there was no such thing as "LPWAN" [9]. Numerous LPWAN systems have emerged in both licensed and unlicensed frequency bands. Today's top emerging technologies, which involve numerous technological variations, are Sigfox, LoRa, and NB-IoT.

Figure 1 shows the comparison of different network technologies, demonstrating how the trade-off between transmission range and data throughput characterizes the wireless communication environment. While cellular networks like 4G and 5G offer high data speeds and short-range protocols like Bluetooth and ZigBee are tailored for specialized activities, they frequently fall short of the unique demands of vast IoT installations, which call for both wide coverage and low energy usage. LPWAN occupies a crucial niche in the Long-range category, as the classification illustrates. Although LPWAN technologies, such as LoRaWAN, have lower data rates than VSAT or cellular systems, they are strategically positioned to support wide-scale connectivity for battery-constrained devices. Because of its special placement, LPWAN is the best option for long-term industrial and environmental monitoring when range and power efficiency are more important than high throughput.

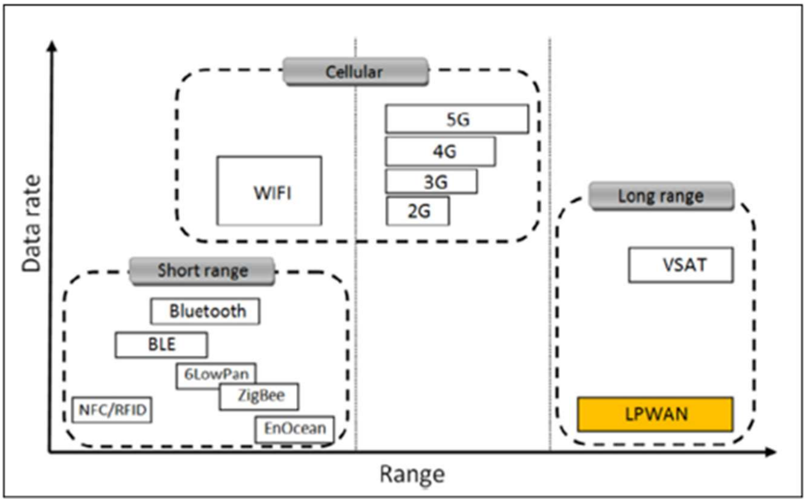

Fig. 1. Required data rate vs. range capacity of radio communication technologies: LPWAN positioning [10]

LoRaWAN is a Media Access Control (MAC) layer protocol. It is a software layer that specifies how devices use the LoRa hardware, such as during transmission and message format [10]. LoRaWAN's strong ecosystem and standardized architecture, which support thousands of end devices per gateway, further solidify its supremacy. LoRaWAN provides more freedom for decentralized networks than licensed alternatives like NB-IoT. Because of this, it has emerged as the industry standard for businesses looking for an affordable way to send tiny data packets across long distances without having to change their batteries very often. LoRaWAN is widely used, but as network density rises, it encounters significant technological obstacles. In dense urban deployments or large-scale industrial locations, this lack of synchronization results in high packet loss, which lowers the network's overall reliability [12]. Additionally, LoRaWAN is quite vulnerable to fading and inter-network interference, especially in settings with a lot of physical barriers. Ineffective spreading factor assignments result from the typical Adaptive Data Rate (ADR) mechanism's frequent inability to respond swiftly enough to dynamic channel conditions. For the "massive IoT" goal, where network stability is crucial, these scalability and interference problems provide a significant obstacle [13].

Semtech Corporation has shown LoRaWAN, an open technology. It is known as a MAC protocol that ensures time scheduling and on-air wireless communication between the network's base station and end nodes. Furthermore, as Figure 2 illustrates, the nodes are widely distributed, creating a star network topology. At the back-end, the gateways relay the received data to their servers. As a result, those nodes may belong to Class A, B, or C, depending on the needs of the application [14].

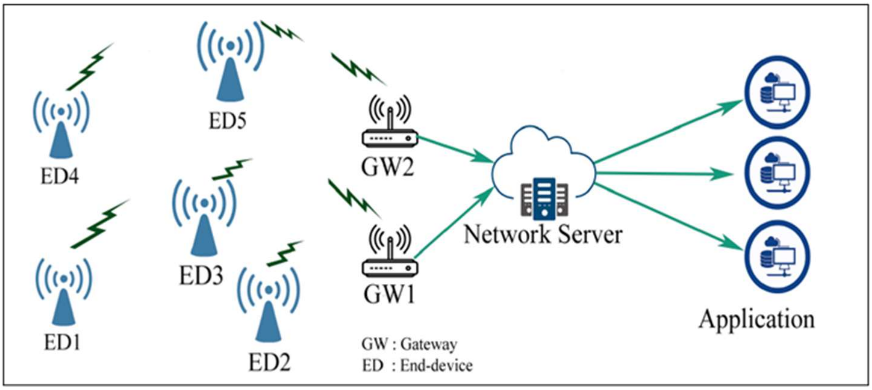

Fig. 2. LoRaWAN network architecture [13]

LoRa is commonly referred to as the physical layer foundation of Semtech's long-range LPWAN technology. Essentially, it spreads several chips throughout the occupied frequency bandwidth using a proprietary CSS-derived technique. LoRa technology uses the fundamental physical-layer modulation technique known as Chirp Spread Spectrum (CSS) to provide reliable, long-range communication at low power. In contrast to conventional modulation techniques, CSS uses wideband linear frequency-modulated pulses, or "chirps," that change in frequency over time to encode data. Significant resistance against multi-path fading, Doppler shifts, and electromagnetic interference is provided by this signal spreading over a larger bandwidth [10]. By encompassing all related frequency bands, the basic chirp instantly modifies its frequency values. Five primary factors are taken into account when integrating the fundamental chirp for LoRa: bandwidth (BW), SFs, CRs, Ptx, and channel signal-to-noise ratio (SNR). A collection of SF ∈ {7, 8, 9, 10, 11, 12}, BWs ∈ {125 kHz, 250 kHz, and 500 kHz}, and CR ∈ {4/5, 4/6, 4/7, 4/8} can be used to choose the SF, BW, and CR, respectively. The modulator generates a variety of chirps, including up- and down-chirps. Concerning the bandwidth, LoRa may transmit a sample every $Tc = \frac{1}{BW}$. This could also indicate how long the chirp lasts.

LoRa has received a lot of interest in the IoT space. The unlicensed industrial-scientific-medical (ISM) frequency ranges are where it works. End nodes (EDs) and their gateway (GW) are directly connected by the IoT-based LoRa network. Usually, these EDs run on batteries. It is important to be able to correctly assess the energy model of the IoT-based LoRa system. Consequently, it has been challenging to determine the optimal LoRa communication parameters to use in the communication of IoT networks [13]. Moreover, several factors have been demonstrated to reduce the performance of LoRaWAN, particularly when changing the position of the device, that is, during the transition between stationary and mobile scenarios. Two of the problems include the boundaries of the standard ADR and the application of conventional heuristic methods, which set the parameters of transmission in case of stable conditions and lead to instability in case of a dynamic network [15].

Moreover, the nodes which are not moving might be unable to respond to sudden alterations in the signal or environment since they do not adapt to such changes in real time. Without the understanding of these dynamic variations, the network can have undue loss of packets, resulting in wastage of energy. Due to unpredictable interference, mobile situations are often considered complex and difficult to manage. The system cannot afford to be ineffective due to failure to adapt, and without intelligent assistance, it will become disheartened and fall. Moreover, the static arrangements are not so vulnerable to the fast-paced demands of the ecosystem of the IR4.0. Unless they are subjected to the elasticity of intelligent algorithms, LoRaWAN systems might not gain the resilience required by the modern autonomous applications. Because of that, it is necessary to switch to more data-driven approaches with less rigid heuristics. Machine learning (ML) is a feasible solution that can allow the network to handle the complexities of interference and evolving environments in real-time, allowing it to provide real-time adaptability and forecasting. ML has turned out to be a groundbreaking approach to network optimization to address these nonlinear and dynamic challenges. Unlike other traditional methods based on heuristics, machine learning models are very precise at predicting the future states of the network and identifying complexities in massive datasets. ML is able to provide intelligent insights, inaccessible to static programming, because of historical transmission data.

The system would need smart assistance to not get discouraged and fail when it cannot change. Moreover, the static configurations are not so subject to the rapid demands of the ecosystem of the IR4.0. LoRaWAN systems might fail to gain the resiliency required by modern autonomous applications unless they are subjected to the flexibility of intelligent algorithms. To elaborate more on this issue, the remainder of this paper is structured as follows: Section 2 addresses the related work of the study, with a focus on the evolution of LoRaWAN and the integration of AI. Section 3 describes the PRISMA protocol and selection criteria, among other features of the systematic review method, in detail. The results of the review are provided in Section 4, based on the chosen themes, such as algorithms and performance parameters. Section 5 discusses the results and the impact of machine learning on the optimization of LoRaWAN. Section 6 underlines the recommendation and wraps up the study.

2 Related Work

Researchers in the field of wireless communication have been focusing more on integrating various ML architectures to achieve optimal performance of LoRaWAN networks. A preliminary search was conducted to ensure that the area of this systematic review has not been well-explored by other literature and that there are sufficient scholarly materials (i.e., peer-reviewed articles and indexed databases) available. The accessibility to major online libraries such as SpringerLink, ScienceDirect and Scopus was verified with the help of the institutional subscriptions; open-access repositories were considered as well to ensure a complete search.

An initial search was done with the string ("LoRa" OR "LoRaWAN") AND ("Machine Learning" OR "Artificial Intelligence" OR "Deep Learning" OR "Intelligent Algorithms") AND ("Optimization" OR "Resource Allocation" OR "Performance") to define the number of relevant materials. Although there are a number of review papers on LoRaWAN optimization and general machine learning applications in IoT, there is still a dearth of systematic syntheses that specifically address the intersection of LoRaWAN algorithm settings. Available review articles were identified and contrasted to ensure the uniqueness of the proposed research problems; Table 1 summarizes their key findings and limitations. This table shows that although a number of reviews and surveys have examined the optimization of LoRaWAN and IoT networks. The majority of previous research, including [16] and [17], ignores the complexity of node mobility in favor of static network configurations or basic security frameworks. Furthermore, the most recent thorough work by [18] offers a general review of LPWAN characteristics. This table also shows that while many evaluations and surveys have looked at LoRaWAN and IoT network optimization, relatively few have specifically explored the application of the algorithms that have been used in the research. According to most of the previous researchers [16, 17], they focus on static networks or basic security structures. Providing an in-depth analysis of trends and challenges, especially during the 20192025 timeframe, this SLR will address the gaps that have been identified.

Table 1. Comparison of existing review papers with the proposed SLR

Author & Year	Focus of the Review	Technology	RL Focus?	Mobile Nodes?	No. of Selected Studies	Period Covered
Maurya et al. [16]	SF allocation schemes	LoRaWAN	No	No	14	2017 – 2022
Rafique et al. [19]	Anomaly Detection in IoT	IoT (General)	Yes (DL/ML)	Limited	31	2016 – 2024
Sowmya et al. [17]	Secure data transfer	LoRaWAN	No	No	14	2019 – 2024
Almalki & Angelides [20]	Synthesis of ML & UAV fleets	DRL & LoRa	Yes	Yes (Drones)	35	2020 – 2024
Diane et al. [18]	LPWAN characteristics & challenges	LPWAN (General)	Limited	Not Specific	7	2015 – 2025

Aparcana-Tasayco et al. [21]	Anomaly detection in IoT	IoT (General)	Yes	Limited	21	2020 – 2025
Mao et al. [22]	LLM applications in LoRa	LoRa (AI)	No	No	10	2021 – 2025
Proposed SLR study	Algorithm trends for LoRaWAN Networks	LoRaWAN	Yes	Yes	53	2019 – 2025

3 Methodology

A proper procedure must be adopted in conducting a Systematic Literature Review (SLR) to ensure that the articles that are to be reviewed are chosen and properly analyzed in relation to the research questions that should be answered with reasonable arguments. The section describes a meticulous procedure for systematically selecting articles, reviewing the research and extracting, analyzing, and interpreting data related to the usage and optimization of LoRaWAN networks. This process ensures that the adaptation of machine learning algorithms to the varying challenges posed by node mobility is systematically studied using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. This methodology gives a strong foundation to integrate the latest state-of-the-art literature, identify performance trends, and develop a future roadmap of autonomous communication protocols in the IoT environment.

Review Protocol. The PRISMA procedure was used to fill out the SLR in this research [23, 24]. PRISMA is one of the frequently used tools to systematically select the published articles to be analyzed, based on some choice criteria, due to its systematic flow of actions. This study applied the PRISMA-based SLR methodology recommended by [25] as an overarching framework to develop the review. PRISMA's goal is to ensure that the papers are selected according to the desired review criteria. Writers should formulate research questions according to PRISMA, since this is the first step in creating the review process. To confirm the validity of the study topics, a preliminary procedure is carried out to make sure they haven't been emphasized by earlier, related efforts. The writers methodically choose the articles to be included in the review based on systematic sequential methods, namely identification, screening, and eligibility, after a set of precise research questions has been formulated and shown to be authentic. After the articles had been reviewed and gathered, a quality assessment procedure was carried out to guarantee the content quality of the chosen articles and make them pertinent to the systematic review's goal. In the end, the chosen themes served as the basis for the data abstraction and analysis.

Formulation of Research Questions. Research questions are crucial to developing an effective review process. Research questions that are too broad may produce unmanageable or overloaded data, while too restricted research questions will result in a lack of resources and information. In order to ensure that the review only provides relevant information about the study and avoids unnecessary repetition, it is imperative to develop a suitable research topic. This review is to explore the machine learning algorithms trends in optimizing LoRaWAN network performance. To provide a clear context for these questions, Figure 3 illustrates the systematic process adopted for this review methodical processes of the systematic literature evaluation. A comprehensive understanding of the study's methodological and technical basis is provided by the merging of these frameworks.

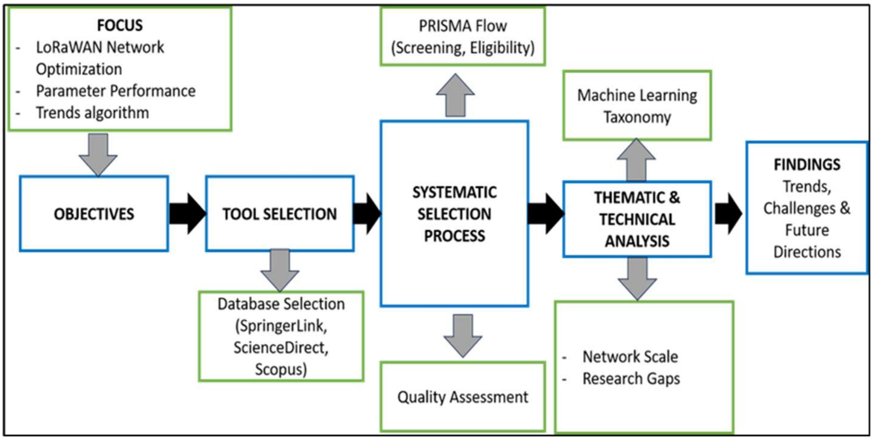

Fig. 3. Systematic process adopted for this review

Therefore, the following four Research Questions (RQs) are established in order to address the trends and issues outlined in this framework:

- RQ1: Which current machine learning algorithms are used in mobile LoRaWAN optimization?
- RQ2: What is the network scale (number of nodes) typically evaluated in current RL-based LoRaWAN research?
- RQ3: What parameters have been used in evaluating the performance of LoRaWAN optimization?
- RQ4: What are the major research gaps in existing optimization algorithms towards the development of reliable LoRaWAN?

To ensure the proposed research objectives are met, this systematic literature review is structured to address specific questions that bridge the gap between current literature and the development of the improved LoRaWAN algorithm.

Systematic Searching Strategies. This study conducted a SLR to evaluate current methods for altering and implementing algorithms for optimizing LoRaWAN networks. The review adhered to the PRISMA procedure, which consists of three main stages: identification, screening, and eligibility, to guarantee a thorough selection of pertinent publications. Only excellent research addressing the difficulties of algorithm optimization is included, thanks to this methodical approach. Figure 4 shows the detailed workflow of the article selection and review procedure used in this study.

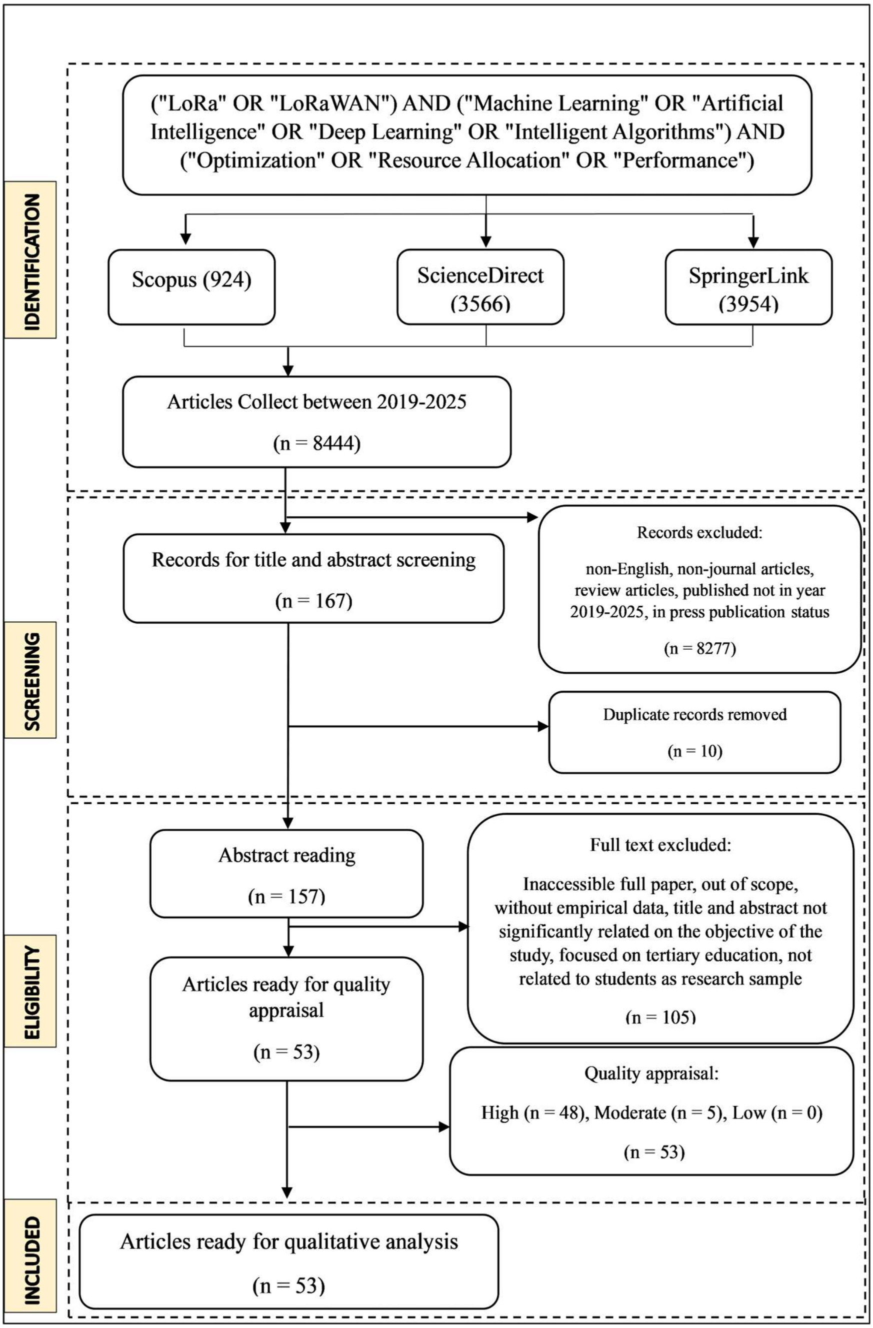

Fig. 4. PRISMA model for systematic review adapted in this study

Identification. The PRISMA protocol's first step is identification, which aims to methodically gather pertinent material for review. Three main databases are Scopus, ScienceDirect, and SpringerLink. This database was chosen for this investigation because of its standing as a thorough archive of excellent, peer-reviewed technical research and because they are compatible with institutional access for effective data extraction. The developed research questions served as the basis for the search strategy, which combined primary keywords [24] and their derivatives, with a particular emphasis on "LoRa/LoRaWAN", "Optimization" and "Algorithm Trends". Boolean operators (AND and OR) and double quotes ("") were used to create a strong search string that was applied to titles, abstracts, and keywords in order to guarantee accuracy. 8,444 records were found for additional screening after this methodical search was limited to the publication window of 2019 to 2025. Table 2 displays the search terms used in this investigation for each of the three databases. All the databases contain identical terms.

Table 2. Search string used for article searching

Database	String
Scopus	("LoRa" OR "LoRaWAN") AND ("Machine Learning" OR "Artificial Intelligence" OR "Deep Learning" OR "Intelligent Algorithms") AND ("Optimization" OR "Resource Allocation" OR "Performance")
ScienceDirect	
SpringerLink	

Screening. The screening step is an important component of the PRISMA system, as specific inclusion and exclusion criteria can narrow down the original search results to the most relevant literature. An initial inspection of the titles and abstracts of the initial 8,444 records resulted in the elimination of 8,277 records that did not qualify for the study. Publications that were not in English, non-journal articles, review articles, articles published prior to 2019 and those with a status of "in-press" were all filtered out. To process the remaining records, all the search results were stored as RIS files and then imported into the Mendeley Desktop. Ten duplicate entries were systematically identified and removed, and this resulted in 157 unique articles to proceed with the next step. A bibliometric analysis with the metadata in the generated RIS files was then performed using the VOSviewer application. Only the best, peer-reviewed journal publications that had been published within the target period were considered to be eligible. A bibliometric analysis conducted using the metadata in the generated RIS files was then performed using the VOSviewer application. Only the best, peer-reviewed journal publications that had been published within the target period were considered to be eligible.

Table 3. Inclusion and exclusion criteria

Criteria	Inclusion Criteria	Exclusion Criteria
Language	English	Non-English
Timeline	Published between 2019 – 2025	Published before 2019

Publication Type	Journal articles and conference proceedings	Non-journal articles (e.g., books, theses)
Article Type	Primary research articles	Review articles
Publication Stage	Final published version	In-press publication status
Study Focus	LoRa/LoRaWAN, Algorithm trends	Out of scope, inaccessible full paper, or studies without empirical data

Eligibility. The screening process resulted in 157 articles being eligible to undergo the evaluation step. This will ensure the content of the selected studies is directly related to the goals and research questions. To ensure that the articles used were relevant, the titles and abstracts were assessed manually. This review removed 105 publications based on various reasons such as inaccessible full papers, studies which were not relevant to the evaluation, insufficient empirical data or titles and abstracts which were irrelevant to the objectives of the study. Articles that did not have students as the main research sample or those focused on post-secondary education were also excluded. Consequently, 53 articles were deemed eligible and fit to be evaluated in terms of quality.

Quality Appraisal. The rest of the 53 articles were forwarded to two external professionals in the field to assess the quality of the articles to ensure that the content in the selected articles used in the eligibility process is of high quality [24]. The quality appraisal process was conducted using an assessment form, and the experts rated the articles on three quality scales that included low, moderate, or high. The specified protocol was followed by considering only publications of moderate or high quality during the final evaluation. The experts assessed 5 articles as intermediate quality and 48 articles as excellent quality. No further articles were removed at this stage as none received a low quality rating. This has led to the inclusion of 53 articles altogether in the qualitative analysis as qualified.

Data Abstraction and Analysis. In order to ensure that the review was able to focus on the primary objectives of the study, relevant information was systematically accessed and analyzed based on the designed research questions. The synthesis of the results was carried out with the help of a thematic analysis that provided the creation of the topics and sub-themes needed to classify the results. The formation of these themes was driven by the observation of patterns in both the literature and the implementation of LoRa networks and reinforcement learning techniques, as illustrated by the bibliometric mapping and keyword co-occurrences in VOSviewer. The themes must appropriately reflect the study questions and resolve any discrepancies in the literature; the author refined them iteratively. Two independent experts in the fields of wireless communication and qualitative research were then given the proposed subject framework to ensure the validity and rigor of the analysis. Both experts affirmed that the themes and sub-themes were sufficient, relevant, and appropriate to respond to the research questions formulated and provide a strong foundation for the ensuing debate.

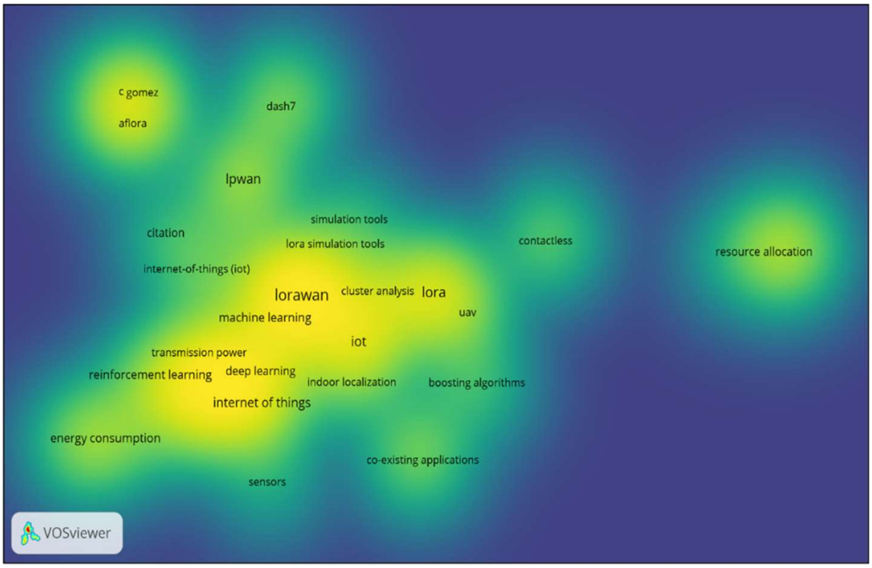

Fig. 5. Keyword Density Visualization Map of Selected Articles

A bibliometric study of the 53 selected articles was performed with the help of the VOSviewer to identify any recurring themes and patterns. In particular, the co-occurrence of author keywords was used to create a Density Visualization map. Keywords such as "Internet of Things," "Reinforcement Learning," and "Machine Learning" appear as high-density areas in Figure 6, as evidenced by the prominent yellow intensity. This figure shows that one of the significant fields of the current research is the incorporation of intelligent codes into IoT systems. Also, the proximity of such phrases as "Energy Efficiency" and "LoRaWAN" speaks of a strong thematic cluster dedicated to the optimization of low-power network communication protocols. This is one of the primary sources of guidance that was used by the author in developing the final theme framework of this review.

4 Results and Findings

The systematic literature review identified a final number of 53 articles that met the inclusion and quality criteria to be included in a qualitative synthesis. These publications are the current state of the research on the integration of the trends of machine learning algorithms in LoRa/LoRaWAN network designs. The themes that were to be discussed were selected based on the thematic analysis and the density visualization of keywords generated by VOSviewer, including nine major themes. These themes include: (1) general publication trends; (2) types of network architecture; (3) algorithms used; (4) LoRa simulation tools; (5) energy efficiency strategies; (6) security and anomaly detection; (7) scalability in IoT networks; (8) performance metrics; and (9) research focus areas. Each theme is explored to provide an in-depth understanding of the benefits of intelligent algorithms in optimizing communications in dynamic IoT settings.

Overall Trend. The Figure 6 presents the number of publications that relate to the implementation of the LoRa/LoRaWAN technology and machine learning in the seven-year period (2019-2025). Due to the increased attention to intelligent optimization of LPWAN, the research sphere tends to have a stable and increasing tendency in general. Though the initial years of the study period were characterized by a steady rise in publications, there was a significant rise in the number of publications in the later years due to the increased prevalence of IoT and ML applications in industrial and smart city settings. This growing momentum indicates that the research community is significantly hastening the creation of autonomous and energy-efficient communication protocols based on machine learning methods. The overall trend reveals that the Reinforcement Learning (RL) and LoRa network synergy domain is rapidly evolving due to the need to have a reliable connection in dynamic and mobile situations.

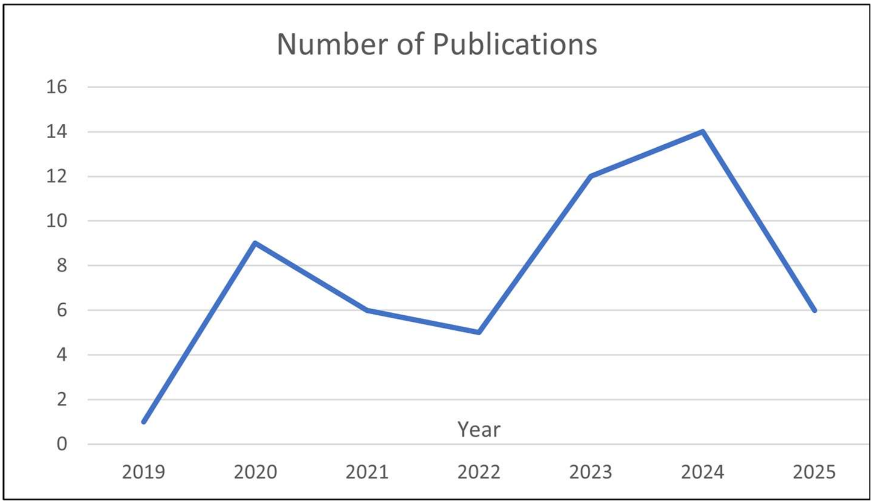

Fig. 6. Number of Publications

The number of articles related to the research field between 2019 and 2025 is shown in the figure. This increase implies that the topic got a lot of traction and attention from researchers, particularly beginning in 2022. A time of rapid expansion and increased scholarly focus is indicated by the dramatic increase from 5 publications in 2022 to 14 in 2024. Nevertheless, the data indicates a drop to six publications in 2025, which may indicate a change in research objectives or a period of stabilization following the peak of the prior year. Table 4 summarizes the selected papers' average citation count, journal name, and number of citations. The number of citations indicates how often the paper has been referenced by other scholars. The average indicates the study's level of popularity from the year of publication to the year included in this SLR (i.e., 2026). The top five most popular studies (indicated by citation average) include [26] with a citation average of 55.2, [27] with a citation average of 55.5, [19] with a citation average of 39.5, [28] with a citation average of 19.5 and [29] with a citation average of 19.5. With 331 citations, [26] is the most cited study overall. The quality of each of the selected articles is verified by Schimago Journal and Country Rank (SJR) quartile, where 28 articles are in Q1 journals, 23 are in Q2 journals, and 2 are in Q3 journals.

Table 4. Summary of the selected articles

No	**Reference (Author, Year)**	**Country**	**Cit.**	**Cit. Avg**	**Journal / Source**	**Q1**	**Q2**	**Q3**	**Q4**
1	Sandoval et al. [30]	Spain	87	12.4	IEEE Transactions on Network and	/			

					Service Management			
2	Park et al. [31]	S. Korea	43	7.2	Eurasip Journal on Wireless Communications and Networking		/	
3	Alenezi et al. [32]	United Kingdom	33	6.0	IET Communications	/		
4	Hussain et al. [26]	Canada	331	55.2	IEEE Communications Surveys and Tutorials	/		
5	Farhad et al. [33]	S. Korea	65	10.8	Sensors		/	
6	Francesca C. et al. [34]	Italy	29	4.8	Computers	/		
7	Nguyen & Kortun [35]	Vietnam	18	3.0	EAI Endorsed Transactions Industrial Networks and Intelligent Systems			/
8	Singh et al. [28]	Belgium	117	19.5	Sensors (Switzerland)		/	
9	Cotrim & Kleinschmidt [36]	Brazil	99	16.5	Sensors (Switzerland)		/	
10	Narieda [37]	Japan	33	5.5	Sensors (Switzerland)		/	
11	Zorbas et al. [38]	Ireland	35	7.0	Sensors (Switzerland)		/	
12	Hamdi et al. [39]	Qatar	63	12.6	IEEE Internet of Things Journal	/		
13	Dantas Silva et al. [40]	Brazil	74	14.8	IEEE Access	/		
14	Beltramelli et al. [41]	Sweden	41	8.2	IEEE Transactions on Instrumentation and Measurement	/		

15	Lluís Casals [42]	Spain	13	2.6	Sensors		/
16	Ghazali et al. [43]	Malaysia	87	17.4	IEEE Access	/	
17	Ali et al. [44]	Pakistan	14	3.5	Entropy	/	
18	Idris & Karunathilake [45]	Germany	40	10.0	Sensors		/
19	Hribar et al. [46]	Ireland	6	1.5	Computer Communications	/	
20	Almuhaya et al. [27]	Malaysia	222	55.5	Electronics (Switzerland)		/
21	Rosenberger et al. [47]	Germany	32	8.0	Sensors		/
22	Acosta-Garcia et al. [48]	Spain	7	2.3	Internet of Things (Netherlands)	/	
23	Xiao et al. [49]	China	4	1.3	Electronics (Switzerland)		/
24	Farhad [50]	South Korea	41	13.7	IEEE Internet of Things Journal	/	
25	Minhaj et al. [51]	Germany	69	23.0	IEEE Access	/	
26	Perković et al. [52]	Croatia	34	11.33	Electronics (Switzerland)		/
27	Wang et al. [53]	China	2	0.67	ACM Transactions on Sensor Networks	/	
28	Piroddi [54]	Italy	10	3.33	Network	/	
29	Halder & Newe [55]	Ireland	29	9.67	Future Generation Computer Systems	/	
30	Farhad & Pyun [56]	S. Korea	40	13.33	Sensors		/
31	Chung & Lim [57]	South Korea	6	2.0	IEEE Access	/	
32	Jiang et al. [58]	China	24	8.0	Digital Communications and Networks	/	

33	Islam et al. [59]	Australia	25	8.33	IET Wireless Sensor Systems		/	
34	Mhatre et al. [60]	United States	1	0.33	Result in engineering	/		
35	Parween & Hussain [61]	India	5	2.5	International Journal of Information Technology (Singapore)		/	
36	Rao & Sundar [62]	India	3	1.5	Engineering Research Express		/	
37	Zholamanov et al. [15]	Kazakhstan	6	3.0	Journal of Sensor and Actuator Networks	/		
38	El-Ebiary et al. [63]	Malaysia	8	4.0	Telkomnika (Telecommunication Computing Electronics and Control)			/
39	Josbert et al. [64]	China	22	11.0	Journal of King Saud University - Computer and Information Sciences	/		
40	Almalki & Angelides [20]	Saudi Arabia	6	3.0	Computing	/		
41	Rostami & Goli-Bidgoli [29]	Iran	39	19.5	Journal of Cloud Computing: Advances, Systems and Applications	/		
42	Munyao et al. [65]	Kenya	7	3.5	Discover Internet of Things		/	
43	Shamshiri et al. [66]	Germany	13	6.5	Discover Applied Sciences		/	
44	Krishna et al. [67]	India	24	12.0	Results in Engineering	/		

45	Kufakunesu et al. [68]	South Africa	8	4.0	Future Internet		/
46	Chowdhury et al. [69]	India	5	2.5	IEEE Access	/	
47	Rafique et al. [19]	United Arab Emirates	79	39.5	Sensors		/
48	Noura et al. [70]	France	5	5.0	Internet of Things and Cyber-Physical Systems	/	
49	Manzil et al. [71]	United Arab Emirates	1	1.0	Internet of Things and Cyber-Physical Systems	/	
50	Khasawneh et al. [72]	Jordan	10	10.0	Discover Internet of Things		/
51	Alkhayyal & Mostafa [73]	Saudi Arabia	0	0.0	Sensors	/	
52	Diane et al. [18]	Senegal	10	10.0	Discover Internet of Things		/
53	Kumar et al. [74]	India	3	3.0	Results in Optics		/

A total of 26 countries has been identified as the authors' affiliation countries from the chosen publications. As shown in Figure 7, researchers from South Korea and India undertake the majority of the research on LoRaWAN optimization using machine learning, providing 10 out of 53 papers, or roughly 19%. The research distribution displayed shows that ML-based LoRaWAN optimization is a topic of global interest and highlights its significance in improving LoRa performance.

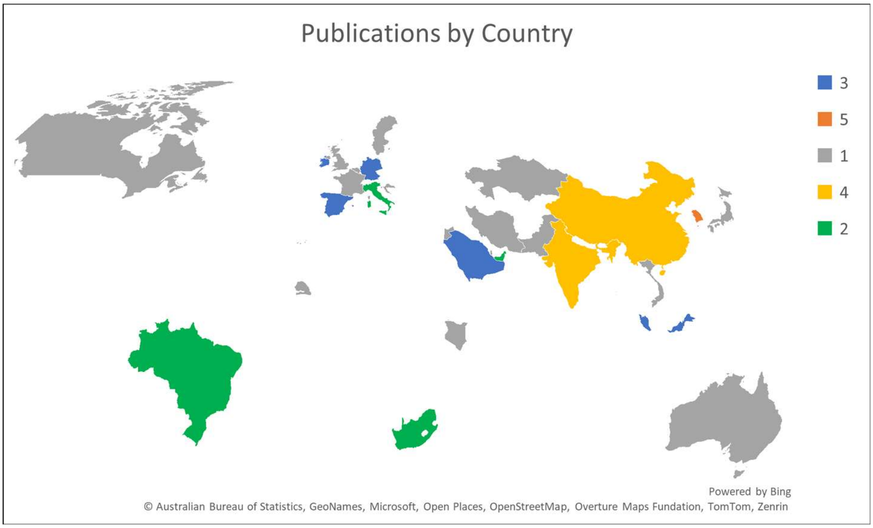

Fig. 7. Number of articles published according to country

Figure 8 illustrates the correlation between the most frequently used terms in the chosen articles. Based on the gathered keywords, VOSviewer co-word analysis produced this network. According to the displayed network of keywords, network parameters (such as spreading factor, transmission power, and adaptive data rate), algorithmic techniques (such as deep Q-networks, genetic algorithms, and reinforcement learning), performance metrics (such as energy efficiency, packet delivery ratio, and latency), and application contexts (such as Internet of Things, Industrial IoT, and mobile node environments) have all been linked to LoRaWAN optimization using machine learning.

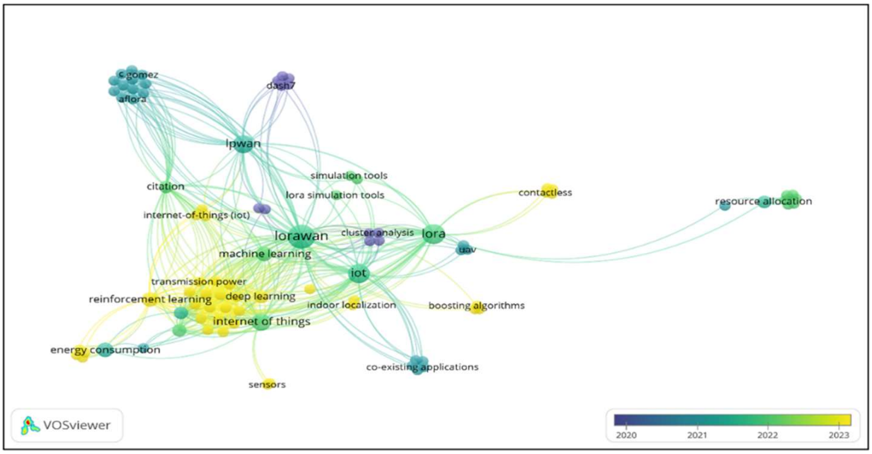

Fig. 8. Network mapped from keywords of the selected articles (Co-word analysis)

Figure 9 represents the distribution of the selected articles according to the different research methodologies and tools utilized in LoRaWAN network optimization. The results showed that the majority of the studies rely heavily on software simulation (32%), followed by review or survey-based studies (30%) and experimental testbeds (26%). A lesser part of the research uses a hybrid method (10%), which is both simulation and real-world data, and only 2% of the articles use mathematical modelling only. The trend is well established that software simulation is the chosen approach since it is scalable and can be used to model the deployment of massive IoT that otherwise would be impractical to deploy physically. As an example, MATLAB and NS-3 are popular for assessing the performance metrics such as throughput and energy efficiency [30, 32]. Conversely, physical hardware-based experimental methods offer important perspectives on signal attenuation in reality and environmental noise [34]. Besides simulators based on software, other researchers concentrate on intensive mathematical modelling to understand the performance of LoRa in adverse conditions. To illustrate, [71] examined the reliability of multihop communication in an underground environment by coming up with mathematical representations of bit error rate (BER) and testing them using numerical simulations. The technique is crucial in estimating the behavior of networks in challenging fading environments prior to any physical implementation. This study points out the applicability of real deployments as empirical data to study the behavior of the LoRaWAN more accurately than theoretical data. The combination of hybrid approaches, albeit small, provides a stronger validation as it provides a bridge between theoretical simulation and hardware outcome [50]. In this way, this distribution shows that there is a strong dependence on the virtual environment in order to push the limits of the LoRaWAN scalability. Table 5 tabulates a detailed list of the 53 articles chosen by their research methods.

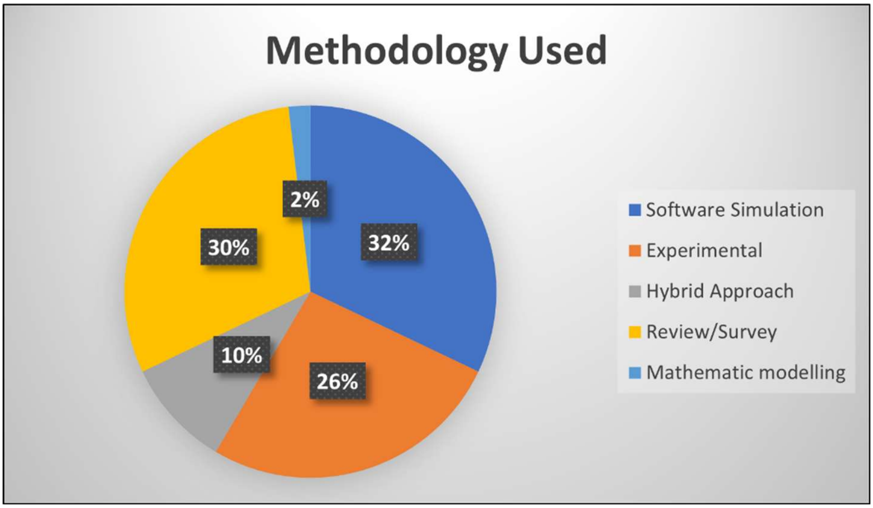

Fig. 9. Article distribution in the methodology used

Table 5. List of articles according to methodology used

Methodology	Reference
Software Simulation	Sandoval et al. [30], Park et al. [31], Alenezi et al. [32], Lluís Casals [42], Ali et al. [44], Hribar et al. [46], Acosta et al. [48], Minhaj et al. [51], Chung & Lim [57], Parween & Hussain [61], Kufakunesu et al. [68], Rao & Sundar [62], Zholamanov et al. [15], Mhatre et al. [60], Manzil et al. [71], Kumar et al. [74], Anwar et al. [75]
Experimental	Francesca et al. [34], Nguyen & Kortun [35], Beltramelli et al. [41], Perković et al. [52], Wang et al. [53], Piroddi [54], Halder & Newe [55], Islam et al. [59], Munyao et al. [65], Shamshiri et al. [66], Chowdhury et al. [69], Khasawneh et al. [72], Alkhayyal & Mostafa [76], Xiao et al. [49]
Hybrid Approach	Farhad et al. [33], Hamdi et al. [39], Rosenberger et al. [47], Almalki & Angelides [20], Krishna et al. [67],
Review/Survey	Hussain et al. [26], Singh et al. [28], Cotrim & Kleinschmidt [36], Narieda [37], Dantas Silva et al. [40], Ghazali et al. [43], Idris & Karunathilake [45],Almuhaya et al. [27], Farhad [50], Jiang et al. [58], El-Ebiary et al. [63], Josbert et al. [64], Rostami & Goli-Bidgoli [29], Rafique et al. [19], Noura et al. [70], Diane et al. [18]
Mathematic Modelling	Zorbas et al. [38]

Result for Research Question. The 53 publications are compiled in this section and thoroughly analyzed to answer the four main research questions of this study. The analysis begins by considering the large variety of algorithms applied in LoRaWAN optimization, especially focusing on the transition to advanced machine learning methods instead of traditional, static methods. It also evaluates the wide spectrum of network sizes that include ultra-dense simulations and localized experimental systems that are used to check these optimization systems. Another classification of performance evaluation is to identify the significant performance indicators that are utilized in the literature to establish the key optimization objectives, including energy efficiency and throughput dependability. Finally, this part will conclude by summarizing the ongoing challenges and limitations of the current literature, providing a basic understanding of the research gaps, particularly in developing effective and reliable algorithms for mobile LoRaWAN conditions.

RQ 1: Algorithms & Optimization of machine learning in LoRaWAN. With 41% of the examined studies using Q-Learning, the data shown in Figure 10 indicates that it is the most often used algorithm. This is mainly because of its low processing requirements for IoT devices. The use of deep learning to control complicated network interference is a major trend, with Deep Q-Networks (DQN) coming in second at 28%. Deep Reinforcement Learning (DRL) and Hybrid/Federated models, on the other hand, have the lowest proportions, at 10% and 6%, respectively, suggesting that although these sophisticated decentralized techniques are developing, they are not yet as widely used as conventional Reinforcement Learning (RL) techniques.

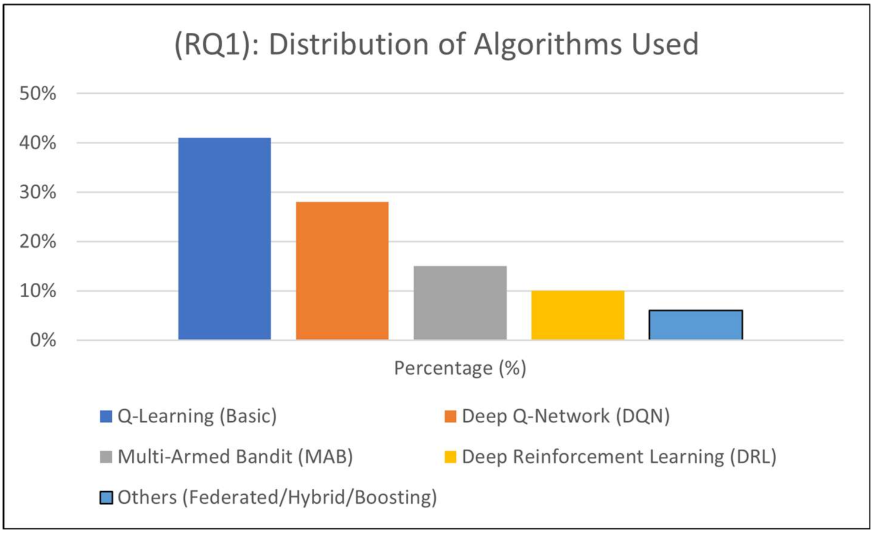

Fig. 10. The most trending algorithm in machine learning

Referring to the first research question (RQ1: What are the current research trends of Machine Learning algorithms for LoRaWAN network optimization?), research in ML-based LoRaWAN optimization has shown a significant increasing trend over the past few years. This expansion is mainly driven by the necessity of smart resource management so that the constraints of the traditional ADR in the high-density and dynamic settings can be surmounted [18]. ML and, in particular, RL can be used to dynamically adjust the transmission parameters, including Spreading Factor (SF) and Transmission Power (TP) and can thus be well suited to a wide range of IoT application scenarios, including smart farming and urban monitoring [13]. Consequently, the incorporation of ML has been shown to be a huge success in the improvement of network Quality of Service (QoS), that is, the improvement of the ratio of the delivery of packets (PDR), the decrease in the latency and the empowerment of energy efficiency. These results were summarized based on a wide range of researchers applying different research methods, the majority of which applied software simulations (32%) running on platforms such as NS-3 and MATLAB, experimental testbeds (26%) and mixed methods (10%). The study includes a variety of network sizes, with small-scale systems of less than 50 nodes [31] and large-scale and ultra-dense systems (thousands of devices) [32]. In comparison of the algorithms distribution, our results revealed that Q-Learning is the most used algorithm because it is the simplest (41%), but that distribution is shifted towards more advanced algorithms, such as DQN and DRL, to address the complexity of modern LoRaWAN architectures.

RQ 2: Network Scale (Number of Nodes). The scales of the network analyzed throughout the selected research are presented in Figure 11. Small Scale (1-50 nodes) has the highest percentage (47%) according to the data, and it may indicate that many researchers still use the controlled laboratory environment. The remaining 13% and 6% are composed of Large Scale and Ultra-Dense settings (including satellite networks), respectively, with Medium Scale (51-500 nodes) following at a distant second with 34%. This illustrates a clear trend where the testing in large-scale, field deployment situations remain relatively limited.

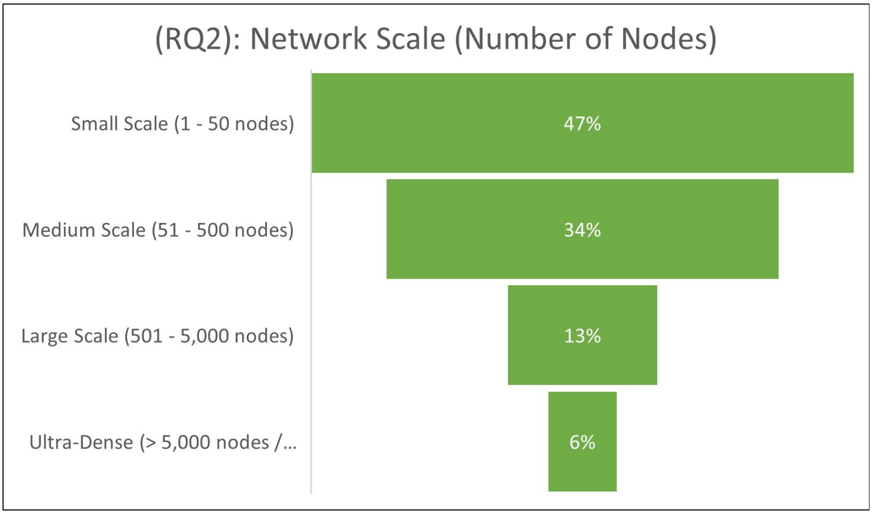

Fig. 11. Network Scale

Based on the second research question (RQ2: What is the distribution of network scales in the existing literature for LoRaWAN optimization?), the study analysis shows that most of the existing research is carried out in small-scale settings (47%), usually with less than 50 nodes [31]. This is then followed by medium-scale deployments (34%) with 51 to 500 nodes. Though the LoRaWAN is intended to support massive connections, a minimal part of the research is carried out on large-scale (13%) and ultra-dense or satellite-integrated networks (6%), which comprise thousands to millions of devices [32, 74]. The high concentration of research on small-scale networks is often motivated by the ease of implementing experimental testbeds and the lower computational complexity required for initial algorithm validation. However, as network density increases, challenges such as packet collisions and inter-network interference become more prominent, rendering conventional management techniques less effective. As a result, recent trends show an increasing effort to shift towards large-scale software simulations to model the scalability limits of LoRaWAN in smart city or industrial scenarios [18]. These findings suggest a critical research gap in validating advanced Machine Learning algorithms, such as DRL, in ultra-dense environments to ensure link reliability and scalability.

RQ 3: Primary Evaluation Parameters. The main performance indicators used to assess LoRaWAN optimization are shown in Figure 12. With 91% of the articles mentioning them, throughput and PDR are the most important parameters. Energy consumption and battery life come in second with 79%. These numbers demonstrate that the main goals of LoRa research are power efficiency and dependability. Measures such as latency (28%) and scalability (23%) are, nevertheless, not as widely talked about, meaning they are often perceived as secondary considerations.

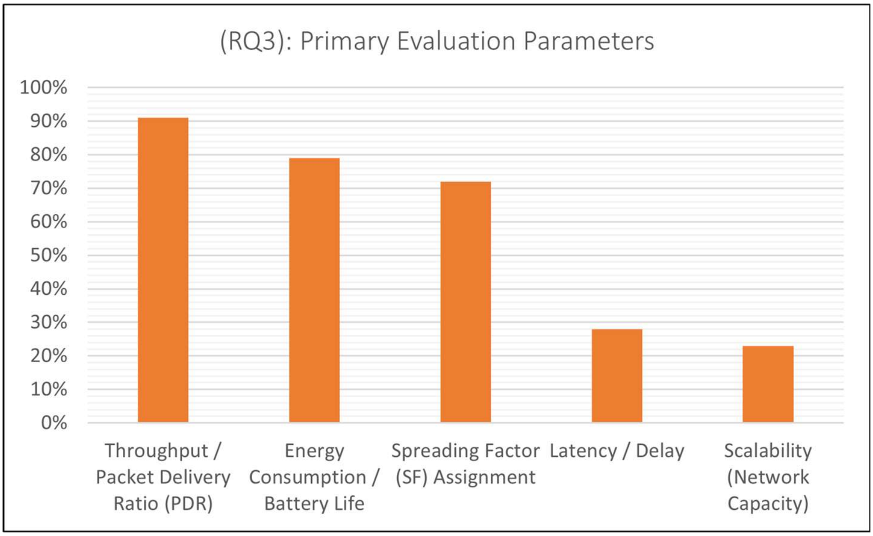

Fig. 12. Primary Evaluation Parameters

In reference to the third research question (RQ3: What are the primary evaluation parameters and performance metrics used in LoRaWAN optimization studies?), our systematic analysis has revealed that the assessment of LoRaWAN performance is largely focused on the reliability of the network and energy sustainability. The findings indicate that an enormous proportion of the chosen research (91%) is focused on Throughput and PDR as the main performance metrics [15, 30]. This is closely followed by Energy Consumption (79%), which is also a critical issue due to the low-power character of LoRaWAN devices. The strong focus on the PDR and energy efficiency is preconditioned by the basic need of the LoRaWAN to provide long-range connectivity with a minimum of a 3-year battery life of end-devices. In more complicated cases with high-density traffic, studies have started to incorporate more advanced measurements like Latency or Delay (28%) and Scalability (23%) to quantify how the network can support increased capacity [33, 75]. Consequently, there has been notable success in balancing these commonly-conflicting KPIs using Machine Learning, such as optimization of SF and TP to minimize interference without energy budgets. These results demonstrate that although the basic connectivity continues to be the priority, the optimization towards network capacity and real-time response is becoming the trend to meet the demands of the advanced IoT applications.

RQ 4: Major Research Gaps. The primary research gaps in the current literature on machine learning-based LoRaWAN are indicated in Figure 13. Sixty percent of the research identified device mobility as the main obstacle to further development, making it the most important gap. Cybersecurity (23%) and the requirement for real-time hardware implementation (19%) are two more significant gaps. However, as the field advances to more complex machine learning mechanisms, the visibility and understandability of these algorithms remain under research, with the relatively small percentage of 8% of Explainable AI (XAI).

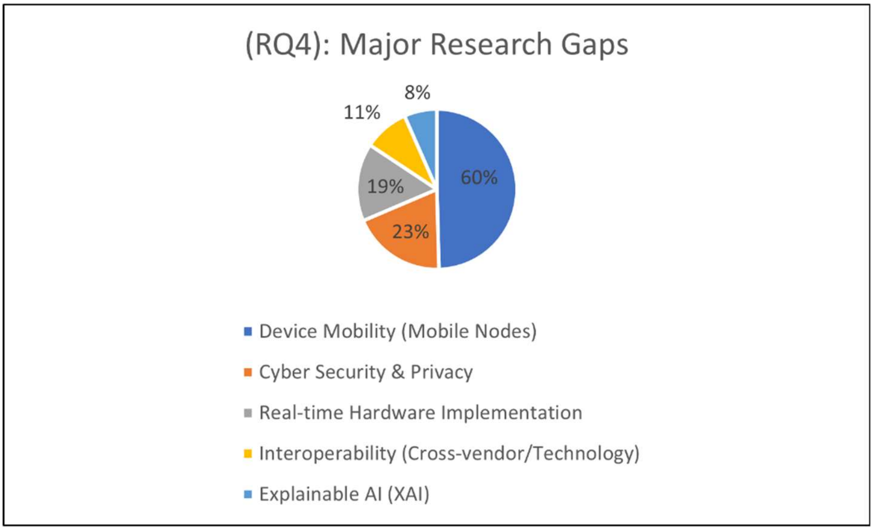

Figure 13: Major Research Gap

Considering the last research question (RQ4: What are the primary research gaps and future directions in Machine Learning-based LoRaWAN optimization?), our systematic review defines several areas of critical interest that are still under-investigated in spite of the increased number of publications. The largest gap observed is that of Device Mobility (60%), where existing Machine Learning and Reinforcement Learning algorithms cannot ensure link reliability and optimal parameter choice even during the motion of the nodes. The current literature is mostly dedicated to the simulation of a static or semi-static scenario, which leaves a significant gap in the effective solutions to dynamic IoT applications. This drawback is also more accentuated by the fact that signal properties in LoRaWAN are strongly dependent on physical movement, as well as environmental variations, and require more adaptive and mobility-conscious optimization models [49].

Besides mobility, the second but essential gaps were defined as Cyber Security and Privacy (23%) and Real-time Hardware Implementation (19%) [19, 67]. Although software simulations can offer a platform on which algorithms can be developed, the absence of empirical validation on physical hardware constrains the practical application of such intelligent systems in the real-world setting. In addition, the new fields like Interoperability (11%) and Explainable AI (8%) are the future of LoRaWAN research as there is an increasing demand to find not only performant models, but also transparent and interoperable between various technology vendors. These results indicate that the next generation of research in this field needs to shift to pure simulation of stationary environments with the creation of mobility and hardware-tested algorithms to achieve the full potential of intelligent LoRaWAN networks.

5 Discussion

RQ1: Machine Learning Algorithms for LoRaWAN Optimisation

For the research question 1, the findings reveal a clear transition from conventional heuristic-based optimisation towards intelligent machine learning approaches for LoRaWAN parameter adaptation. Q-Learning remains the dominant algorithm, accounting for 41% of the reviewed literature, followed by DQN at 28% among the 53 selected studies. This suggests that RL has become the preferred optimisation paradigm because of its ability to dynamically adapt transmission parameters according to changing network conditions. Several studies consistently reported that Q-Learning effectively improves network reliability while maintaining low computational complexity, making it particularly suitable for resource-constrained LoRaWAN end devices. Conversely, studies employing DQN demonstrated superior performance in dense and highly dynamic environments by handling larger state spaces and more complex interference patterns. These findings indicate a gradual shift from lightweight reinforcement learning algorithms towards more sophisticated deep reinforcement learning models as LoRaWAN deployments become increasingly complex.

Due to this transition, the literature reveals an important trade-off between optimisation capability and computational efficiency. Although DQN improves adaptation to complex network conditions, its higher computational overhead, increased memory requirements, and longer training time may limit its deployment on resource-constrained LoRaWAN end devices. Such requirements may limit its applicability in battery-powered IoT devices with limited processing capability. Consequently, most practical implementations continue to favour lightweight reinforcement learning algorithms despite the increasing popularity of deep learning approaches. This contradiction highlights that algorithm selection depends not only on optimisation performance but also on the computational constraints of the target LoRaWAN application. Therefore, future research should focus on developing lightweight intelligent optimisation algorithms capable of achieving high adaptability while maintaining low energy consumption and computational overhead.

RQ2: Network Scale Evaluated in Existing Studies

The analysis demonstrates that existing LoRaWAN optimisation research is predominantly validated using small-scale network deployments. While medium-scale networks accounted for approximately one-third of the selected publications, nearly half of the reviewed studies evaluated fewer than 50 nodes. This highlighted the need for the researchers continue to rely on controlled simulation environments and laboratory testbeds because they provide lower implementation costs and simpler experimental validation. The algorithm performance can be evaluated efficiently under predefined network conditions using platforms such as NS-3 and MATLAB simulation-based studies. However, only a limited number of studies investigated large-scale or ultra-dense LoRaWAN environments consisting of hundreds or thousands of devices. One of the limitations is because of hardware cost, infrastructure requirements, and deployment complexity, which is although LoRaWAN was originally designed to support massive IoT connectivity. Hence, increasing network density intensifies packet collisions, channel interference, and scalability issues, thereby reducing the effectiveness of conventional optimization methods. Consequently, the current literature provides limited evidence regarding the robustness of reinforcement learning algorithms in realistic large-scale Industrial IoT deployments. This finding highlights the need for future research to validate optimisation algorithms using larger and more heterogeneous network environments that better represent practical deployment scenarios.

RQ3: Performance Evaluation Parameters

The reviewed studies consistently prioritised communication reliability and energy efficiency as the primary objectives of LoRaWAN optimisation. PDR, throughput, and energy consumption were the most frequently evaluated performance metrics, indicating that maintaining reliable communication while extending battery lifetime remains the principal concern of existing optimisation research. This common focus reflects the operational characteristics of LoRaWAN, where low-power communication and long-term autonomous operation are fundamental design requirements. Several studies further demonstrated that reinforcement learning algorithms successfully improve these performance indicators through adaptive selection of transmission parameters such as Spreading Factor and Transmission Power. Nevertheless, other important performance indicators received considerably less attention. Metrics such as latency, scalability, fairness, convergence time, and recovery time were evaluated by only a relatively small proportion of studies. This imbalance suggests that many optimisation algorithms remain focused on improving individual performance objectives rather than providing comprehensive network optimisation. In highly dynamic IoT applications involving mobile devices, optimising a single performance metric may not sufficiently address the multiple challenges associated with changing wireless channel conditions. Therefore, future optimisation frameworks should adopt multi-objective optimisation strategies capable of simultaneously balancing communication reliability, energy efficiency, latency, scalability, and network stability.

RQ4: Research Gaps and Future Directions

The synthesis of the selected studies identifies several important research gaps that remain insufficiently addressed within current LoRaWAN optimisation research. Although reinforcement learning algorithms have demonstrated promising improvements over conventional ADR mechanisms, most existing studies continue to assume static or semi-static network environments. Only a limited number of studies explicitly considered highly mobile LoRaWAN applications, despite the growing adoption of IoT technologies in intelligent transportation, asset tracking, autonomous robotics, and industrial automation. Rapid fluctuations in signal quality caused by node mobility often prevent conventional reinforcement learning models from converging efficiently, thereby reducing optimisation performance under dynamic operating conditions. Another significant limitation concerns the limited adoption of advanced multi-objective optimisation and decentralised learning approaches. Most existing studies optimise only a single communication parameter or focus on a limited set of performance metrics, while joint optimisation of Spreading Factor, Transmission Power, Packet Delivery Ratio, and energy consumption remains relatively underexplored. Similarly, although FL has recently emerged as a promising solution for privacy-preserving and distributed optimisation, its practical application within LoRaWAN networks is still in its early stages. For the future research, these findings suggest that to investigate mobility-aware reinforcement learning, FL, and multi-objective optimisation frameworks capable of supporting large-scale, heterogeneous, and highly dynamic LoRaWAN deployments. This enables an expected development to improve network adaptability, communication reliability, and energy efficiency while addressing the practical requirements of next-generation IIoT applications.

Table 6 summarizes the popular reinforcement learning algorithms in the LoRaWAN ecosystem based on their focus on optimization. The analysis demonstrates that the choice of algorithms and the operational constraints of the network are well coordinated. Q-Learning and Multi-Armed Bandit (MAB) models, for instance, are largely applied to end-devices with small resources due to their low memory footprint and computational simplicity. Conversely, DQN are increasingly being deployed to increasingly complex problems like intense signal interference and dynamically allocating resources in crowded environments. Federated Learning is also a new trend that is identified in the table and is a response to the growing demand in terms of data privacy and decentralized optimization. This mapping demonstrates the current development of LoRaWAN optimization towards a multi-tier intelligent architecture, when the complexity of the algorithm is tailored to the specific needs of the IoT application.

Table 6. Summary of the selected articles

Optimization Focus	Trending Algorithms	Discussion / Observation
Resource Constraints	Q-Learning, MAB	Low memory overhead makes it ideal for end devices, but it performs poorly in high-density networks.
High Interference	DQN, DRL	Very efficient at allocating SF/TP, but it needs a lot of processing power, usually at the gateway level.
Decentralization	Federated Learning	This algorithm is still in the early stages of development for LoRaWAN, but it is emerging as a solution for local processing and privacy.

6 Conclusion

The optimization of the LoRaWAN network with machine learning has garnered a lot of attention among researchers in the world in efforts to address the scalability and energy constraints inherent in IoT networks. In order to gather and generalize the work of other researchers in a systematic way, this study conducted a systematic literature review that covered the most recent tendencies and mechanisms of optimization of the LoRaWAN performance. According to the PRISMA model, 53 articles were identified and processed according to a number of major themes, such as the trends in research, types of algorithms, scale of networks, and performance indicators. The following themes were studied to find out the effect of artificial intelligence, which offers intelligent solutions to optimize network parameters in dynamic settings. This paper review results indicate that the tendency towards the optimization of ML-based LoRaWAN has grown considerably in the past few years. The chosen study emphasizes the idea that DQN have become the trendiest method of managing more complicated and dynamic environments because they are superior in optimization in resource-constrained environments. The studies focus on the balance of Packet Delivery Ratio (PDR), Throughput, and Energy Consumption in the view of network performance. Additionally, our paper tests the suggested algorithms at varying network sizes, which will give a concise description of how smart adjustment will reduce collision parameters and ensure the overall stability of a stand-still and mobile LoRaWAN ecosystem.

Besides the stringent contribution of this research, a number of limitations to future research may be taken into account. First, although DQN offers major performance benefits, this research paper recognizes an urgent need to shift to FL models to respond to the increasing data privacy-related concerns and decentralized computing at the network edge. Secondly, Hardware-in-the-Loop (HIL) testing has a conspicuous gap; therefore, future studies should focus on filling the gap between the theoretical AI models and large-scale industrial applications by integrating real hardware with realistic simulations. Lastly, although this review is based on 2D modeling of networks, future research ought to take into consideration 3D scattering environments as well as mobility-aware models to further streamline the mobility of the gateways to attain a real "Green IoT" paradigm.

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